Asset Class Impacts on the 30-Year Efficient Frontier

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We investigate the long-term (30-year) efficient frontier weights in five common asset class indexes by adding classes one-by-one to the stock-bond frontier. Our results show that bonds are the most effective diversifier for stocks, real estate is helpful only at higher risk levels, and international stocks and commodities add little diversification benefits over the longer time horizon. Overall, our results highlight the difficulties using modern portfolio theory to quantify asset class allocations.

The efficient frontier (the highest expected return for a given standard deviation), holds a sacred place in academic finance and has driven much of the world's movement towards increased diversification. Further, diversification across broad asset classes (stocks, bonds, cash, commodities and real estate for example) is commonly believed to account for the vast majority of long-term portfolio returns and picking the right assets within asset classes for only a smaller proportion. Given the means, standard deviation and covariance's of the asset classes, mathematical programming can solve for the weights in the asset classes for different levels of risk tolerance (portfolio standard deviation) so the portfolio is "optimized" (has the highest return/risk profile).

A central issue for this research is that asset class weights calculated using the efficient frontier do not significantly differ depending on the combination of asset classes chosen to estimate the inputs (asset class mean return, standard deviation, and covariance). Many efficient portfolios have zero weights in most asset classes and huge weights in others, seemingly contradictory for a theory that touts diversification.

Variability in asset class weights is well documented in a vast academic literature, but much of the published research in this area considers only stock diversification or stock/bond diversification issues, not the more practical problem of portfolio weights across a broader, commonly-employed spectrum of asset classes. The emphasis for this study is to document the contribution that commonly employed asset classes make to the standard stock/bond efficient frontier.

By utilizing index returns for the last thirty years, we construct efficient frontiers that add asset classes one-by-one to the stock-bond frontier. We find that only real estate makes a significant contribution to the risk/return tradeoff inherent on the stock/bond portfolio (international stocks and commodities offer little improvements). Though the benefits of diversifying across asset classes are obvious in our graphs, bonds are the basic long-term diversifier for stocks. The results highlight the difficulty inherent in using the historical returns to set target weights for portfolio construction going forward.

LITERATURE REVIEW

Portfolio optimization techniques are commonly used by sophisticated money managers as a first step in the process of creating a portfolio for new clients. Given the investor's risk tolerance, portfolio optimization solves for the weights in various asset classes so that the overall portfolio has the highest expected return for the given standard deviation. Optimization techniques are seldom, if ever, employed at the level of individual assets; the resulting large covariance matrices are cumbersome without some serious computing power and many believe covariances for individual assets are too transitory for the past to be reasonable estimates of the future. Common academic wisdom is that asset class weights are far more important than picking the right individual assets, though that contention is not without debate (Ibbotson and Kaplan, 2000; Hood, 2005). In practical applications, the asset class weights derived from the optimization calculations are called "strategic" or long-term weights, which are then adjusted by "tactical" or short-term rationales based on over/under valued asset class metrics or the forecast for the macro economy and associated sensitivities of the asset classes (Haugen, 2001, pp. 177-194). Many financial advisors attempt to sell their ability to predict the future with expensive tactical allocation strategies.

The finance literature has long documented the extreme sensitivity of asset class weights to changes in input variables (asset class means and the covariance matrix). For example, "A surprisingly small increase in the mean of just one asset drives half the securities from the portfolio. Yet the portfolio expected return and standard deviation are virtually unchanged." (Best and Grauer, 1991, p. 315). The current literature often concentrates on high-powered econometric methods (Bayesian statistics and "shrinking" the covariance matrix) to estimate the inputs. Despite the extra mathematical rigor, overall results show that these strategies do not consistently outperform the simple strategy of allocating 1/N to each asset class (DeMiguel, Garlappi and Uppal. 2007).

Even though optimization methodologies are relatively quantitative in nature there seems to be little consensus about which are the appropriate asset classes; they range from the simple stocks versus bonds to 15-25 different classes that might parse domestic stocks into nine different classes with bond classes also stratified by term and credit risk. Real estate, commodities and venture capital are often separate asset classes. Evidence from professional investors is scant since they like to hedge their pronouncements and seldom provide hard strategic asset allocation targets. Target date (or lifestyle) mutual funds supply some evidence about the diffuse nature of professional advice, however, since they are designed to be an investor's entire portfolio and automatically switch from relatively risky assets (usually stocks) to safer assets (mostly bonds) as the "target" date approaches (commonly called a "glide path"). Evidence from target date funds shows little consensus for the appropriate asset classes and wild variations in the optimal asset class weights for different funds with the same target date (Maher, White and Schooley, 2010).

Asset class diversification has received extra scrutiny in the last few years for a bad reason; it generally failed to help avoid large portfolio losses in the 2008-2009 liquidity crisis and its aftermath. Two different problems have been posited as key contributors to the poor results. First, correlations between asset classes change dramatically when stock markets have large gains (low correlations) versus when they have large losses (high correlation). Secondly, returns distributions are fat-tailed with far more extreme losses/gains than predicted by the normal distribution. The correlation issue is commonly classified as the "new normal" with "risk off" (good market conditions) and "risk on" (bad) regimes (Page and Taborsky, 2010). There are several corollaries to the fat-tailed returns distribution argument, including volatility clusters and return distribution skewness (different sized positive/negative tails) (Stoyana et. al., 2011).

Even sophisticated diversification strategies such as the “Yale model” cracked under the pressure of the 2008-2009 economic downdraft. In the 2000s, the Yale University endowment leader, Dave Swensen, became the guru of investing into a wide range of alternative assets, including illiquid assets like hedge funds, natural resources and private equity. The basic arguments were that liquidity was overpriced for long-term investors and alternative investments provide low correlations (and increased diversification benefits) for standard asset classes like stocks and bonds (Leibowitz, Bova and Hammond, 2010). Though the Yale endowment performed admirably over the entire decade through 2009, it lost almost 25% in the year ending June 30, 2009. Basically, correlations between asset classes increased dramatically in the liquidity crisis (Page and Taborsky, 2010) and endowment portfolios traded like the traditional 60 % stock / 40% bond fund in the boom and then were more volatile in the bust (Coggan, 2011).

The recent failure of asset class diversification strategies has led to new research attempting to link systematic risk and asset allocation. The key empirical properties on contagion (systematic risk) are developed, but practical implications for asset allocation are scarce. One approach is to “diversify trends” by linking expectations of different asset classes to macroeconomic variables (Fabozzi and Focaardi, 2010). Another is to employ risk factors (yield curve variables, commodities, credit quality spreads, swap spreads etc.) rather than asset classes. Research shows the risk factors are less correlated with equity markets than asset classes, especially in market downturns (Page and Taborsky, 2010). But effective diversification across risk factors still involves a crystal ball into the future, a prospect less appealing given the spectacular collective failures to foresee the future revealed over the past decade.

DATA AND METHODOLOGY

To examine the correlations and resulting risk return profiles of different assets class combinations, the monthly returns on five asset class indices were obtained from Morningstar’s ENCORR database for the period January 1979 to January 2012. The indices are the Russell 3000 stock index, the Morningstar Long-Only Commodities index, the BarCap Aggregate Bond Index of bond returns, the MSCI EAFE Index of international stock returns, and the FTSE NAREIT All REIT Index of real estate returns. All indices are total returns monthly for the time period.

The monthly returns data was used to generate the variance-covariance matrix and the correlation matrix in Tables 1 and 2. The monthly returns data was also employed to calculate the asset class weights that minimize the probability of a loss and minimize portfolio variance (Table 3). An equal weight portfolio was created from the monthly returns data and the probability of loss, return, and variance are shown in Table 3. In addition, Table 3 details the weights for an expected monthly return of 0.008 for the entire period and its probability of loss. Finally, the expected return and standard deviation of each asset class is reported in Table 4.

TABLE 1
VARIANCE-COVARIANCE MATRIX

Variance-Covariance Matrix	*BarCap US Agg Bond TR USD (Total Return)*	*Russell 3000 TR USD (Total Return)*	*MSCI EAFE USD (Price Return)*	*FTSE NAREIT All REITs TR (Total Return)*	*Morningstar Long-Only Commodity TR (Total Return)*
BarCap US Agg Bond TR USD (Total Return)	0.000269	0.000146	0.000128	0.000164	-0.000039
Russell 3000 TR USD (Total Return)	0.000146	0.002107	0.001550	0.001387	0.000434
MSCI EAFE USD (Price Return)	0.000128	0.001550	0.002633	0.001204	0.000640
FTSE NAREIT All REITs TR (Total Return)	0.000164	0.001387	0.001204	0.002430	0.000458
Morningstar Long-Only Commodity TR (Total Return)	-0.000039	0.000434	0.000640	0.000458	0.001892

TABLE 2
CORRELATION MATRIX

Correlation Matrix	*BarCap US Agg Bond TR USD (Total Return)*	*Russell 3000 TR USD (Total Return)*	*MSCI EAFE USD (Price Return)*	*FTSE NAREIT All REITs TR (Total Return)*	*Morningstar Long-Only Commodity TR (Total Return)*
BarCap US Agg Bond TR USD (Total Return)	1				
Russell 3000 TR USD (Total Return)	0.194238	1			
MSCI EAFE USD (Price Return)	0.152008	0.657943	1		
FTSE NAREIT All REITs TR (Total Return)	0.203113	0.613062	0.475746	1	
Morningstar Long-Only Commodity TR (Total Return)	-0.054498	0.217391	0.286805	0.213565	1

TABLE 3
MEANS, EXPECTED RETURNS, AND WEIGHTS FOR CONSTRUCTED PORTFOLIOS

Minimize Probability of a Loss

Asset Class	*US Agg Bond*	*Russell 3000*	*MSCI EAFE*	*FTSE NAREIT*	*Long Commodity*
Weight	0.8343	0.0494	0.0000	0.0127	0.1036

Probability of A Loss = 0.32288. Expected Return = 0.006959. Portfolio Variance = 0.00022292

Minimum Portfolio Variance

Asset Class	*US Agg Bond*	*Russell 3000*	*MSCI EAFE*	*FTSE NAREIT*	*Long Commodity*
Weight	0.8469	0.0211	0.0001	0.0000	0.1320

Probability of a Loss = 0.324126. Expected Return = 0.0068538. Portfolio Variance = 0.00022572

Equal Weights

Asset Class	*US Agg Bond*	*Russell 3000*	*MSCI EAFE*	*FTSE NAREIT*	*Long Commodity*
Weight	0.2	0.2	0.2	0.2	0.2

Probability of a Loss = 0.403737. Expected Return = 0.007142. Portfolio Variance = 0.00086

Required Return of 0.008

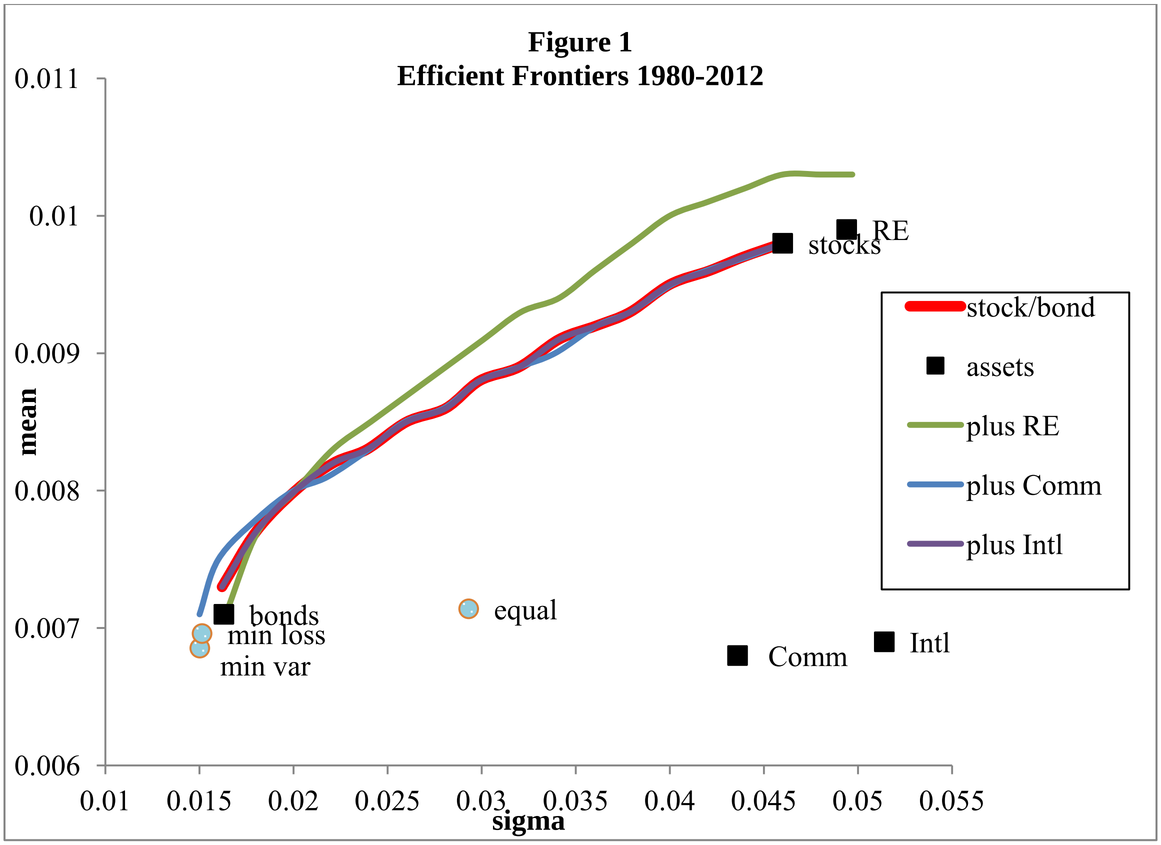
Asset Class	*US Agg Bond*	*Russell 3000*	*MSCI EAFE*	*FTSE NAREIT*	*Long Commodity*
Weight	0.4102	0.3970	0.0000	0.1929	0.0000

Probability of a Loss = 0.38536. Expected Return = 0.008. Portfolio Variance = 0.0007536

TABLE 4
MONTHLY PORTFOLIO MEANS AND SIGMA

	Means	**Sigma**
Bonds	0.0071	0.0163
Stks	0.0098	0.046
RE	0.0099	0.0494
Intl	0.0069	0.0514
Comm	0.0068	0.0436
min variance	0.006854	0.01502
min loss	0.00696	0.01514
equal weights	0.00714	0.02931

The Morningstar Optimizer program from their ENCORR suite was used to generate the minimum variance portfolios in Figure 1. The program restricts asset class weights to positive values and calculates the weights necessary to minimize portfolio variance at each expected return. The data was run independently for each of the portfolio combinations. Bonds and stocks were run to find minimum variance portfolios then each asset class was added independently to the bond and stock combination to generate the additional efficient investment frontiers in Figure 1.



RESULTS

Table 1 (variance-covariance matrix) and Table 2 (correlation matrix) delineate the co-relationships between monthly returns for all five asset classes over the entire 32 year period (1980-2012). Table 2 shows that bonds have a low correlation (0.19) with stocks, thus increasing the advantages of diversifying between these two asset classes. In fact, bonds have a relatively low correlation with all four other asset classes (all below 0.203), including a negative correlation (-0.05) with commodities. Real estate (0.66) and international stocks (0.61) both had relatively high correlations with stocks, reducing their benefit as portfolio diversifiers.

Adding asset class means and expected returns together with the variance-covariance matrix allows us to calculate efficient frontiers. The graph of efficient frontiers (Figure 1) shows four different frontiers, stocks/bonds and then stocks/bonds with each of the other three asset classes added in turn, thus creating three more frontiers. The four frontiers are: 1) stocks/bonds, 2) stocks/bonds/RE, 3) stocks/bonds/Intl, and 4) stocks/bonds/Comm. In addition, the graph charts and labels each of the five different asset classes and three other constructed portfolios; one with the weights optimized for minimum loss (min loss), one with minimum variance weights (min var) and a third with equal weights (equal). Table 3 shows means, sigmas and asset class weights for the three constructed portfolios. Table 4 depicts means and expected returns for each of the five individual asset classes, along with the three constructed portfolios.

Most surprisingly, Figure 1 indicates that only real estate added significant portfolio performance to the efficient frontier. When international stocks and commodities are added to stock/bonds (one at a time), the efficient frontiers essentially mirror the stock/bond frontier (they are almost indistinguishable on the graph). Commodities and international asset classes had low means and high sigmas, and international assets were also relatively highly correlated with US stocks. Real estate was the highest expected return asset class over the entire 32 year period (whew—takes your breath away to see more evidence of the monster bubble in real estate—even with recent stupendous declines, RE is still a good long-term performer) and a significant contributor to high return—high risk efficient portfolios. It's clear that asset classes beyond stocks/bonds, despite the drumbeat for asset class diversification, have had dubious value for long-term improvement in the risk-return tradeoff. In fact, abstracting from real estate, the two efficient frontiers that add an asset class to stock/bonds essentially look like the stock/bond combination line.

There is another way to say the same thing: bonds are the best asset class portfolio diversifier. Despite its low mean return, bonds' low sigma and, more importantly, relatively low correlation with other asset classes, make it the most important piece of any portfolio diversification strategy.

Figure 1 also plots three different constructed portfolios that vary weights in the five asset classes in a systematic fashion: 1) an equally weighted portfolio, 2) a portfolio with weights optimized to minimize the probability of loss, and 3) a portfolio that minimizes the variance of portfolio returns. Table 3 shows that the min-loss and min-variance portfolios are dominated by investments in bonds. The equally-weighted portfolio was a poor performer, mirroring the weak returns in commodities and international stocks, despite some evidence that equally-weighted portfolios perform as well as mean-variance optimization procedures (DeMiguel, Garlappi and Uppal. 2007). Taken as a whole, this evidence supports the view, emphasized by failure of asset class diversification in the 2008 liquidity crisis, that bonds are the basic asset class diversifier for US stocks, in the long-run and the short-run.

CONCLUSION

Our results cast some doubt on the long-term effectiveness of diversification across asset classes (besides bonds) to improve portfolio return-to-risk characteristics. Bonds are by far the most effective asset class for diversifying US stock portfolios. The equally weighted asset class portfolio performs poorly and minimum loss and minimum variance portfolios are dominated by bonds and seem to offer few portfolio benefits beyond that supplied by bonds. Indirectly, our results highlight that the impotence of modern portfolio theory to help pick the optimal mix of asset classes—unless you can predict asset class means, sigmas and covariances—and recent evidence shows how hard that is—MPT is an elegant theory looking for some accurate data inputs.

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